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Investment Manager Skill in Small-Cap Equities

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Keywords: SMALL-CAP EQUITY FUNDS; TRADING ACTIVITY; INVESTMENT PERFORMANCE; ACTIVE PORTFOLIO MANAGEMENT.

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1. Introduction

Do active managers have the requisite skills to successfully outperform the market? This question has been rigorously debated in both academic and practitioner communities for a number of decades. Despite a large number of empirical studies[1] showing that the average active mutual fund does not provide investors with superior risk-adjusted returns to a passive investment strategy (even before management costs are considered), more recent evidence suggests the existence of some value in active management.[2] In the small-cap industry, a number of studies report alphas which are both economically and statistically significant. These include U.S. evidence by Keim (1999), Christopherson *et al.* (2002) and Gorman (2003), and European evidence by Dahlquist *et al.* (2000), Otten and Bams (2002) and Engstrom (2004). The range of outperformance reported across these studies is documented to be between 1.65 and 3.2 percent per annum.

Recent research has investigated investment manager skill using a trade-level analysis of fund performance, inferred from changes in monthly or quarterly portfolio holdings. These studies suggest active funds earn abnormal returns that, at least, partially account for the investment expenses incurred in active management. In particular, Wermers' (2000) evidence for U.S. mutual funds provides support for the Grossman and Stiglitz (1980) informational efficiency equilibrium. Both Pinnuck (2003) and Gallagher and Looi (2006) document superior stock selection ability for active Australian equity managers. Specifically, Gallagher and Looi (2006) report that, on average, active Australian managed funds outperform passive benchmark portfolios and that managers' stock picking ability is stronger in stocks ranked 101-150 by market capitalisation. The opportunities for exploiting private information in these companies may be higher due to the fact that these stocks are less liquid, and analyst coverage is lower compared to larger stocks.

Given the recent evidence documenting active funds' ability to exceed benchmark returns, this study examines an important and growing segment of the active investment industry – the small-cap equity

[1] See, for example, Jensen (1968), Malkiel (1995), Gruber (1996), and Ferson and Schadt (1996).
[2] Studies include Grinblatt and Titman (1989), Daniel *et al.* (1997), and Wermers (2000).

universe. The Australian case is interesting in a number of respects. First, it represents a market where active managers have been spectacularly successful in beating the market across the investment universe.[3] Second, the Australian small-cap industry approximately doubled in size in the two-year period to June 2004, with the total value of wholesale and retail small-cap funds (benchmarking to the Australian Small Ordinaries Index) exceeding $A4 billion.[4] The size of these funds has continued to grow through to 2007 with an annual growth rate of more than 12%.[5] Third, the composition and structure of the Australian small-cap equity market is different to that of the U.S. market. Although the Small Ordinaries Index in Australia (by GICS classification) is concentrated in Industrials, Financials and Consumer Discretionary (like the Russell 2000 Index for small-cap U.S. stocks), the Australian index is heavily weighted towards Property Trusts (the largest sector which accounts for approximately 15% of the index value).[6] Fourth, our study has access to a unique and proprietary dataset comprising the daily trades and monthly portfolio holdings of a representative sample of small-cap equity managers. Utilising this unique dataset of monthly stockholdings and the daily transactions of active small-cap equity managers in Australia, we provide new evidence on the extent to which market efficiency prevails for stocks that have lower levels of information flow and analyst coverage, albeit significant institutional participation. Further motivation for the examination of small-cap management is the work of Bennett *et al.* (2003), which documents that, in recent times, institutional investors in the U.S. have increased their preference toward small-cap stocks as a strategy of chasing perceived mispricing in these securities relative to large stocks. Our research therefore provides a further examination of small-cap fund management ability.

Methodologically, our study extends the literature by considering three different units of observation in evaluating managerial skill, namely returns-based measures, portfolio holdings and daily

[3] Source: Mercer Investment Consulting Manager Performance Analytics (MPA) for Australian Small-cap Equity Managers.
[4] This represents approximately 7% of the small-cap equity market capitalisation as at 30 June 2004.
[5] This information is retrieved from www.investorweb.com.au
[6] According to GICS, the largest five sectors in Australia for the Small Ordinaries Index are Property Trusts, Industrials, Financials, Consumer Discretionary and Gold. For the Russell 2000 Index, the largest five sectors are Financials, Information Technology, Consumer Discretionary, Industrials and Health Care.

transactions. This unification of various performance metrics represents a significant contribution to the performance evaluation literature. Indeed, Kothari and Warner (2001) and Pástor and Stambaugh (2002a, 2002b) identify potential biases arising from returns-based measures.[7] Further, Gallagher and Looi (2006) argue that there are possible limitations from inferring trades from quarterly or monthly portfolio holdings because such measures do not capture intra-period trading. To our knowledge, only Gallagher and Looi (2006) have employed data of the same granularity in performance evaluation, although their research examines active funds which are oriented towards larger-cap equities. Our study also provides an important contribution by considering how the abnormal returns generated by active small-cap managers may be explained due to differences in the liquidity of the underlying stocks, and the relative size of trade packages (i.e., a proxy for information signal value). In addition, our analysis controls for a new variable in risk models that can be applied to performance evaluation studies examining funds investing in stocks exhibiting lower liquidity.

A feature of the small-cap equity industry is that firms which have lower levels of liquidity have more significant transaction costs. Since the seminal work of Banz (1981), a number of studies have argued that the return premium from small stocks is due to the lower liquidity offered by such securities, and this risk proxy has also been considered in a number of asset pricing models.[8] This has led to a number of researchers, including Stoll and Whaley (1983), Fouse (1989), Sinquefield (1991), and Aitken and Ferris (1991), calling into question whether the small-firm premium is an exploitable strategy, given that smaller companies have lower liquidity, wider bid-ask spreads, and therefore significantly greater transaction costs which can substantially erode returns. Other studies have sought to solve the premium puzzle by considering the role of measurement and statistical errors (see for example Roll 1981, 1983; Reinganum, 1981, 1982; and Blume and Stambaugh, 1983)

[7] For example, Kothari and Warner (2001) argue that returns-based (regressions-based) measures have limited ability to detect abnormal fund performance due to large standard errors of the intercept estimates (alphas), especially when a fund's style characteristics differ from those of the value-weighted market portfolio. However, the use of characteristics- and trades-based measures can help improve the power to detect abnormal returns.

[8] See, for example, Ahimud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan *et al.* (1998), Chordia *et al.* (2001), Ahimud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Chan and Faff (2003).

tax loss selling (e.g., Roll, 1983; and Brown *et al.*, 1983) and informational asymmetries (see, e.g., Klein and Bawa, 1977; and Banz, 1981). In addition, market impact costs incurred by institutions have been shown to vary according to factors such as trade size, investment style and market conditions (e.g., Chan and Lakonishok, 1995; Keim and Madhavan, 1997; and Chiyachantana *et al.*, 2004). Other price impact research by Frino *et al.* (2005; 2006)) examines block trades, as well as the components of trading costs (information versus liquidity) by both passive and active money management institutions on the Australian Securities Exchange (ASX). Frino *et al.* (2005) examine the price asymmetry between block purchases and block sales, showing bid/ask bounce effects explain the asymmetry. Frino *et al.* (2006) find that price impact costs for index funds and active funds are different, where index funds have higher temporary price effects (and no permanent price impact) given their liquidity-motivated nature, whereas active managers trading on information exhibit overall price impact costs which are permanent.

We find evidence from the Australian market which is consistent with active small-cap equity managers exhibiting superior stock picking skill. Our results are robust to trading costs given the transaction prices achieved by fund managers trading stocks already account for implicit transaction costs. Using the same dataset, Comerton-Forde *et al.* (2006) show that the principal-weighted average round-trip transaction costs were 1.29 percent, which are significantly higher than the costs for larger stocks (i.e. Aitken and Frino (1996) and Comerton-Forde *et al.* (2005) report round-trip transaction costs of 0.27 percent and 0.50 percent, respectively). Our conclusions concerning managerial ability are also consistent with the Australian evidence documented by Gallagher and Looi (2006) and Pinnuck (2003) for larger-cap oriented funds, which also show that purchases exceed the performance from sales in a fund's alpha generation.[9] We also find the risk-adjusted abnormal returns generated by small-cap equity funds are 59.6 basis points using a five factor model on aggregate returns. In contrast to more larger-cap oriented funds, Pinnuck (2003) documents

[9] Interestingly, Pinnuck (2003) shows that the source of value-add comes from fund managers' holdings in large stocks rather than small stocks. While Gallagher and Looi (2006) also show that the large stocks generate high abnormal returns (1-50 market capitalization rank), the area of greatest skill for larger-cap oriented mandates is in the investment universe 101-150 by market capitalization.

monthly fund alphas of between 0.16 and 0.24 basis points per month using three portfolio holding performance evaluation metrics. However, Pinnuck (2003) also uses a separate sample of net fund returns (after expenses), and for this sample he shows alphas not significantly different from zero. The small-cap fund alphas in this study vary according to the performance model adopted and dimension of data used (i.e., returns, holdings or trades). These results remain both statistically and economically significant even after accounting for management expenses of 8.4 basis points per month and implicit trading costs related to market impact.[10] Our findings show that active small-cap equity managers have been able to exploit information advantages, both successfully and consistently, across the majority of institutional providers. Our evidence therefore provides empirical support for the Grossman-Stiglitz (1980) informational equilibrium view of markets. Further, we also examine the importance of liquidity as a risk factor in performance models. Our results indicate that, even after controlling for liquidity, active small-cap managers exhibit superior stock selection ability.

The remainder of the paper is organised as follows. Section 2 provides a description of the data and a summary of daily trading activities of the active small-cap equity managers in our sample. Section 3 outlines the research design. Section 4 provides the empirical results from the examination of active small-cap managers' performance. Section 5 concludes the study and provides suggestions for future research.

2. Data and Institutional Background

Data are obtained from three sources: Mercer Investment Consulting, the Portfolio Analytics database, and the Securities Industry Research Centre of Asia-Pacific (SIRCA). The Mercer Manager Performance Analytics (Mercer) database provides pre-expense monthly returns of 40 active Australian small-cap equity funds, both surviving and non-surviving, over the period 1991 to 2004 (i.e., "Full Sample"). These funds are benchmarked to the S&P/ASX Small Ordinaries

[10] Average management fee (monthly) for the universe of wholesale Australian small-cap equity funds in 2004.

Accumulation Index. Funds from the Mercer database are included in our sample providing each fund has a minimum of 12 consecutive monthly returns between January 1991 and March 2004. The resulting sample contains 34 active small-cap funds, using all data since the inception of the funds (i.e., "Sample A"). We denote "Sample B" to represent small-cap equity funds for which we also have portfolio holdings and trade data, and these comprise 12 funds out of the universe of funds in the market. Table 1 provides a summary of the performance data for the funds examined in this study. The results from Table 1 illustrate that the pre-expense returns across all sub-samples exhibit a high level of consistency, and are similar to that of the complete universe (i.e., "Full Sample"). Further, the differences between the mean pre-expense return of the complete universe and that of the respective sub-samples are not statistically significant. This illustrates the sub-samples do not display a selection bias. More importantly, there is no survivorship bias in the databases used in this study as Mercer's Australian databases are managed to ensure non-survivors are retained in the data.

<<INSERT TABLE 1>>

This study also performs analysis on a subset of managers in the Mercer universe, using both the month-end portfolio holdings and daily transactions data. This confidential information is sourced from the Portfolio Analytics Database. This sub-sample (i.e., "Sample B") comprises individual month-end portfolio holdings (and daily transactions) for 13 (12) active open-end Australian small-cap equity funds. The number of unique institutions contributing portfolio holdings data (trading data) is 11 (10). The resulting dataset contains a total of 52,190 unpackaged trades and 30,968 month-end holding entries. In total, the 13 active Australian small-cap equity funds have in excess of $A1.73 billion under management, with the average fund size in excess of $A133 million and the largest and smallest funds managing $A411 million and $A8 million, respectively. Table 2 shows that 27.6% (in value terms) of these funds' assets are invested in stocks outside the Small Ordinaries Index, on average. Within the small-cap universe, the capital invested in stocks increases monotonically with firm size with nearly 33% of fund holdings within the largest 25% of small-cap firms.

<<INSERT TABLE 2>>

The period of analysis where we have more granular data is from January 1998 to March 2004. Table 3 presents summary statistics showing the frequency distribution for purchases (Panel A) and sales (Panel B) over time by trade package and by order value. Trade packages represent aggregated daily trades in the same stock where trades occur in the same direction, and that are executed over multiple days (following the method of Chan and Lakonishok, 1995). The trade level analysis illustrates that packages are executed over more than one day, and that trade package duration is a positive function of trade size. Purchases and sales are executed at approximately the same rate by trade frequency and package value. It is also noteworthy that a significant component of the total package value remained incomplete two weeks after the trading commenced (17.1 percent for buys and 17.4 percent for sells). This means that small-cap managers still trade a material quantity of their orders beyond the second week. Panel C of Table 3 shows information on fund trading activity and portfolio turnover. It is shown that active small-cap managers indeed engage in a high degree of portfolio turnover (where turnover is defined as the quotient of all trading divided by the average annual fund size). These results illustrate that small-cap managers turn over their portfolios between 1.02 times and 2.37 times per annum.

<<INSERT TABLE 3>>

Information on ASX stocks is procured from the Stock Exchange Automated Trading System (SEATS) through SIRCA. In addition, the Aspect Financial database is also used to source accounting-related information to determine book-to-market equity ratios. In terms of the risk-adjusted performance techniques outlined in the research design, characteristic-matched benchmark portfolios are formed with reference to stocks comprising the S&P/ASX Small Ordinaries Index.

The Australian small-cap equity market accounts for a small fraction (less than 6%) of the total market capitalisation of stocks listed on ASX. Small-cap stocks are often characterised as exhibiting relatively lower trade volume and trade frequency compared to larger stocks. The S&P/ASX Small

Ordinaries Index is an aggregate representation of the small-cap equity market with a market capitalisation value of $A32.46 billion at 30 December 1994 (consisting of 217 stocks). This grew to $A80.31 billion by 30 September 2005 (consisting of 202 stocks). By comparison, as at 30 December 1994, 100 constituents of the S&P/ASX 100 Index had a market value of $A228 billion, which increased to $791.87 billion by 30 September 2005. The S&P/ASX 300 Index is the combination of the S&P/ASX Small Ordinaries Index and the S&P/ASX 100 Index. Table 4 presents a comparison of ASX trading in small-cap, large-cap, and micro-cap equities.[11] Table 4 shows that the liquidity in the Australian small-cap equity market is sufficient for institutional managers to actively participate in this segment of the market. On average, each of these small-cap stocks traded 58 (70) times per day, with an average daily trading volume of 470,263 (690,594) shares over the last four years (12 months) to 30 June 2004. Interestingly, liquidity has been increasing for small-cap stocks, relative to larger-cap stocks, over time.

<<INSERT TABLE 4>>

3. Research Design

This study examines the performance of small-cap equity managers using different performance metrics across three distinct units of observation: aggregate fund returns, month-end portfolio holdings, and daily transactions.

3.1 Holdings-Based Performance Measures

Holdings-based performance estimates are constructed to evaluate whether managers own stocks that generate returns in excess of an appropriate characteristic-matched benchmark portfolio. The abnormal return generated by manager *j* in month *t* is defined as follows;

$$AR_{jt} = \sum_{i=1}^{N} w_{i,t-1}(r_{i,t} - r_t^{DGTW(i),t-1}) \quad (1)$$

[11] Micro-cap stocks are defined in this study as stocks that are constituents of the S&P/ASX All Ordinaries Index but are outside the S&P/ASX 300 Index.

where $w_{i,t-1}$ is the portfolio weight for stock *i* at the end of month *t – 1*, $r_{i,t}$ is the month *t* return of stock *i*, and $r_t^{DGTW(i),t-1}$ is the month *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* in month *t-1*. Characteristic-matched benchmark portfolios are formed on a value-weighted basis using the All Ordinaries Index through a triple-sort across the dimensions of "size", "book-to-market", and "momentum".[12] This study follows the approach outlined in Daniel *et al.* (1997) in constructing the characteristic-matched benchmark portfolios. Using the S&P/ASX All Ordinaries Index as the reference index, 24 benchmark portfolios are constructed on a monthly basis.[13] The All Ordinaries Index is selected as the reference index, to ensure that benchmark portfolios reflect both the actual holdings and trading activities of underlying managers.[14] This approach is motivated by the findings of Elton *et al*. (1993) who report that "spurious" inferences of performance can arise due to mispecified benchmarks.[15]

Motivated by Chen *et al*. (2000) and Pinnuck (2003), our study also examines the performance of inferred trades executed by managers by considering the changes in portfolio holdings between successive months. These authors argue that one will normally expect active trades to better

[12] Due to the results derived from the five-factor model which includes liquidity, this study elects to omit a sort across the fourth "illiquidity" risk dimension when forming the characteristic benchmark portfolios. Moreover, an added risk dimension will, arguably, have an adverse effect on the benchmark portfolios formed, in that, the added dimension will increase the concentration of the benchmark portfolios, thus making it more prone to misspecification errors.

[13] On each formation date, the universe of stocks in the All Ordinaries Index is first sorted into quartiles based on each stock's market-capitalisation immediately prior to the formation date. Thereafter, the stocks within each size quartile are further partitioned into three individual portfolios based on their respective book-to-market ratio. This ratio is calculated using the book-value of the underlying stock at the end of the firm's financial year during the calendar year preceding the formation date, and the market value (i.e., market-capitalisation) of the stock at the end of the preceding December. Finally, the stocks within each of the 12 portfolios (partitioned by size and book-to-market) are then further divided into two more portfolios based on the stocks' prior twelve-month return, giving a total of 24 characteristic-matched benchmark portfolios. The portfolios are constructed on a value-weighted basis so as to avoid over-emphasising returns generated by smaller positions of the managers. Prior studies such as Pinnuck (2003) use a 5 x 4 x 3 benchmark portfolio split to construct 60 characteristic-matched portfolios, resulting in approximately ten stocks in each portfolio. However, it is important to note that unlike the US stock market, on average, the constituents of the All Ordinaries Index do not tend to exceed 500 stocks. Given the concentration of the Australian stock market, Gallagher and Looi (2006) also argue that it is more appropriate to have smaller number of portfolios and sufficiently large number of stocks in each portfolio so that the benchmark portfolios are not overweighted by large stocks. As a result, the 4 x 3 x 2 benchmark portfolio split employed in this study (i.e., 24 benchmark portfolios with approximately 20 stocks in each portfolio) is more appropriate as it ensures that each benchmark portfolio will be made up of a sufficient number of stocks.

[14] Preliminary tests found that around 35% of the actual stocks held by the small-cap managers in this sample are outside the Small Ordinaries Index, and moreover, approximately 30% of stocks bought by small-cap managers in this sample are also outside the Small Ordinaries Index.

[15] In a similar vein, Gruber (1996), when discussing multi-factor models, argues that selected factors employed in multi-factor regression models should be reflective of the major type of assets held by the funds under examination, and warns that failure to do so can lead to substantially biased performance measures.

represent the existence of private information compared to their aggregate holdings at period end. A positive (negative) trade value represents a "purchase" ("sale") trade. Algebraically, inferred trades can be identified using the following equation;

$$IT_{ijt} = w_{ijt} - w_{ijt-1} \quad (2)$$

where IT_{ijt} refers to the inferred trade measure for stock *i* of manager *j* at time *t*, and w_{ijt} and w_{ijt-1} refer to the portfolio weights for stock *i* at the end of months *t* and *t - 1* respectively.[16]

3.2 Transactions-Based Performance Measures

Gallagher and Looi (2006) report evidence that inferred trades from monthly or quarterly portfolio holdings do not perfectly account for a manager's total intra-period trading. To overcome this issue, Gallagher and Looi (2006) examine performance using a more refined level of data – the daily transactions of funds benchmarked to the S&P/ASX300 index. This study follows the approach outlined in Gallagher and Looi (2006) to examine the value of short-term information represented by the actual trading decisions of small-cap equity funds. Because daily trades are expected to be executed over several days, we proxy an institution's orders by aggregating trades into trade packages using Chan and Lakonishok's (1995) trade packaging methodology.

A similar approach to the method outlined in Section 3.1 is adopted to calculate the daily abnormal returns generated by the underlying stocks in each trade package. The mean daily abnormal return across the entire evaluation period is calculated using the individual daily abnormal returns generated by the underlying stocks across all trade packages. Cumulative abnormal returns (CARs) are then formulated as the sum of the mean daily abnormal returns across the accumulation period, where the reference dates for the CARs are procured from both the start and end dates of the respective trade packages. Algebraically, abnormal returns are calculated as follows;

[16] This approach is consistent with the method used by Pinnuck (2003).

$$\overline{AR_t} = \sum_{j=1}^{L}\sum_{t=1}^{D_j}(r_{ij,t} - r_t^{DGTW(ij),t-1}) \Big/ N \tag{3}$$

where $\overline{AR_t}$ is the mean daily abnormal return for day *t*, $r_{ij,t}$ is the day *t* return of stock *i* for manager *j*, $r_t^{DGTW(ij),t-1}$ is the day *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* for manager *j* on day *t*, *L* represents the total number of underlying stocks traded across the entire sample, D_j represents the number of multiple trade packages in the same stock across different time periods and managers, and *N* is the total number of trade packages in the entire sample. Hence, algebraically, CARs are calculated as follows;

$$CAR_T = \sum_{t=1}^{T} \overline{AR}_t \tag{4}$$

where CAR_T is the cumulative abnormal return between day *t* and day *T*, inclusive. Adjustments to the test statistics for the CARs are made following the approach outlined in Gregory *et al.* (1994). Their procedure makes corrections for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

3.3 Returns-Based Performance Measures

In this study, returns-based estimates are calculated using traditional risk models. The performance estimates are risk-adjusted returns based on the pre-expense performance of the funds in the sample. The single-factor model measures the risk-adjusted return due to the stock-selection ability of managers, where the level of managerial skill is reflected by the magnitude of the alpha. The single-factor regression model is specified as follows;

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \varepsilon_{i,t} \tag{5}$$

where $r_{i,t}$ and $r_{m,t}$ are the pre-expense monthly return of fund *i* and the monthly return on the S&P/ASX Small Ordinaries Accumulation Index (in excess of the monthly RBA risk-free rate), respectively, α_i is the unconditional alpha for the model and β_{iSO} is the systematic risk factor using the Small Ordinaries Index.

In order to ensure the robustness of our results, this study also examines performance using the unconditional multi-factor model. The four-factor model used in this study employs specific factors similar to those outlined in Elton *et al.* (1996), Gruber (1996) and Carhart (1997), and is expressed as:

$$r_{i,t} = \alpha_i + \beta_{iSO} r_{m,t} + \beta_{iSML} SML_t + \beta_{iGMV} GMV_t + \beta_{iPR1YR} PR1YR_t + \varepsilon_{it} \quad (6)$$

where *SML*, *GMV* and *PR1YR* are factor-mimicking portfolios (zero net investments) designed to capture "size", "growth versus value" and "momentum" effects, respectively. The β_i's are the estimated sensitivities of fund *i*'s *return* to the respective factors. The *SML* factor is constructed as the difference between returns of the S&P/ASX Small Ordinaries Accumulation Index and the S&P/ASX 100 Accumulation Index. The *GMV* factor is the return difference between a portfolio of growth stocks and a portfolio of value stocks based on the Citigroup Global Markets Australian Small-cap Growth and Value indices. The *PR1YR* factor is constructed as the return difference between the equally-weighted portfolio of stocks performing in the top 20% and of those performing in the bottom 20% of the S&P/ASX Small Ordinaries Index in the previous 11 months, lagged one-month. All factors are reformed on a monthly basis.

We also contribute to the literature by considering the importance of liquidity as a risk factor in the performance models. Controlling for liquidity is motivated by the fact that smaller stocks trade less frequently than larger securities, as well as the seminal work of Amihud and Mendelson (1986). More recently, Chan and Faff (2003) present evidence showing turnover (a proxy for market liquidity) is negatively related to stock returns in the Australian market. Accordingly, we include a market liquidity factor as a fifth risk control variable to improve the estimates of risk-adjusted performance for small-cap equity funds. The five-factor model is specified as follows;

$$r_{i,t} = \alpha_i + \beta_{iSO} r_{m,t} + \beta_{iSML} SML_t + \beta_{iGMV} GMV_t + \beta_{iPR1YR} PR1YR_t + \beta_{iIML} IML_t + \varepsilon_{it} \quad (7)$$

where *IML* is the factor-mimicking portfolio (zero net investment) designed to capture the "illiquidity" effect of smaller stocks, and β_{iIML} is the factor loading on the liquidity variable (*IML*). The *IML* factor is constructed as the difference in returns between the equally-weighted portfolio of stocks comprising the top 20% and of those comprising the bottom 20% of the S&P/ASX Small Ordinaries Index, ranked by their average daily turnover in the previous month. The *IML* factor is also reformed on a monthly basis.

4. Empirical Results

4.1 Results of Holdings-Based Estimations

This section examines small-cap equity managers' skill utilising monthly portfolio holdings data from January 1998 to March 2004 (i.e., 75 months). Table 5 presents the mean abnormal returns, which are estimated at an aggregate level across the respective evaluation periods.[17] The results demonstrate that, on average, funds in the sample generate positive abnormal returns over the six-month period, with the mean abnormal return over the first three months being significantly positive. More importantly, the mean abnormal returns are also economically significant. For example, the mean abnormal return earned over the first month is more than 38 basis points, which is equivalent to an annualised return of approximately five percent. These results are consistent with previous literature in finding that the stocks held by fund managers generate subsequent outperformance.[18] Overall, the results reveal that managers possess stock picking talent.

<<INSERT TABLE 5>>

We next examine fund performance by testing more informative trade-based estimates. Specifically, trades are inferred from changes in the level of holdings across consecutive holding periods, whereby

[17] The reader may expect the number of observations to be 900 (i.e., 12 funds x 75 months), however, the actual number of observations is lower as a number of funds were established during the sample period. Therefore the sample is clustered towards the latter part of the sample period.

[18] See, for example, Daniel *et al.* (1997), Chen *et al.* (2000) and Pinnuck (2003). Although the magnitude of abnormal returns is slightly higher in this study, the difference is most likely explained by the difference in the investment universes being examined.

a positive (negative) change implies a "buy" ("sell") trade. Table 6 (Panel A) documents that the mean abnormal returns for stocks from "buy" trades are consistently positive across all six evaluation periods, with the first period exhibiting a mean abnormal return that is both positive and statistically significant (59.7 basis points). In contrast, the results for "sell" trades demonstrate that most of the subsequent mean abnormal returns generated by stocks are negative.

<<INSERT TABLE 6>>

We also examine the relative performance based on fund managers' trade package size in Table 6 (Panel B). This analysis is conducted because large and medium-sized trades, on average, are more likely to reflect private information held by the manager, whereas smaller trades are more likely to be liquidity motivated. Indeed, Chakravarty (2001) finds a disproportionate number of informed trades are associated medium-sized trades. We define a "Large" trade as a trade that has an underlying dollar value greater than A$1,000,000. A "Medium" trade is defined as a trade with an underlying dollar value between A$100,000 and A$1,000,000, and a "Small" trade is a trade with a value less than A$100,000.[19] Interestingly, the results in Panel B show that the mean abnormal return of "Medium" buy trades is comparatively larger than that of "Large" buy trades. One potential explanation for this finding relates to the relative size and illiquid nature of the Australian small-cap equity market. It is arguable that, due to the characteristics of the small-cap market, it becomes increasingly difficult for managers operating in this market to execute large trades, without being adversely affected by price impact.[20] Overall, the results presented in Table 6 (Panel B) indicate that small-cap managers are successful at undertaking both small- and medium-sized trade packages. This is supported by the finding that stocks purchased in both categories generate mostly positive mean abnormal returns in subsequent evaluation periods (particularly over the initial four months),

[19] These values are selected taking into consideration the size of the market in which small-cap managers operate. In addition, we also conduct tests on a relative trade size basis.

[20] Indeed, some prior studies find larger (more complex) trades incur a significantly higher level of price impact. See, for example, Chan and Lakonishok (1995).

while stocks sold in both categories generate mostly negative mean abnormal returns (particularly over the first two months).

4.2 Results of Transactions-Based Estimations

This section reports the results derived from employing the performance evaluation procedure outlined in Gallagher and Looi (2006). The use of daily transaction data facilitates the examination of the value of short-term information content that is associated with each decision to trade. However, there is a major issue concerning the use of individual transactions as the basis for formulating performance measures. This issue arises because, for institutional investors, a moderately sized position in a stock (relative to the market) can represent a significant portion of the stock's total daily trading volume (this especially applies to small-cap stocks). Therefore, it is a normal practice amongst investment managers to split orders into smaller parcels. The concern for performance studies is therefore the need to aggregate individual daily transactions in a meaningful manner that will enable the identification of the aggregated order. We follow the approach outlined in Chan and Lakonishok (1995) to group trades into "packages" which reflect the desired order quantity to be traded given a common information signal.

Performance using trade data is examined across two separate event windows. The first window utilises the start date of each trade package as its reference date, and starts 60 days before that date (hereafter referred to as [Day (-60 to 0)]). The second window utilises the end date of each trade package as the reference date and ends 60 days after that date (hereafter referred to as [Day (0 to +60)]. Adjustments to fund performance with respect to "priced" risk factors is undertaken using Daniel *et al.* (1997) characteristic-matched benchmark portfolios formed along the risk dimensions of "size", "book-to-market" and "momentum". In the spirit of the CAPM, and the type of portfolio holdings of small-cap managers, we consider the broader S&P/ASX All Ordinaries Index as being an important reference portfolio in constructing these characteristic-matched benchmark portfolios.

Abnormal returns are calculated on a daily basis as the difference between the buy-and-hold returns of the underlying stocks and those of the corresponding characteristic-matched benchmark portfolios. Individual daily abnormal returns are then aggregated over the respective accumulation periods to formulate the CARs.

Table 7 presents summary statistics concerning the daily abnormal returns generated by stocks traded by active Australian small-cap equity managers. The results for the window [Day (0 to +60)] demonstrate that, on average, abnormal returns for stocks purchased are positive for 42 days (out of the 60-day event window), of which 16 days also exhibit statistical significance. Comparatively, there are 18 days with negative abnormal returns; however, none of these are statistically significant. Given that the mean daily abnormal return is also highly economically significant (i.e., 2.1 basis points per day is equivalent to approximately 46 basis points per month), these results corroborate our earlier finding that active small-cap equity managers are capable of identifying and exploiting mispriced securities.[21]

<<INSERT TABLE 7>>

Table 8 reports the CARs over selected accumulation periods. This trades-based performance metric enables a more detailed analysis of the timeframe during which the private information possessed by active small-cap managers is generated in the market. The results for the period [Day (0 to +60)] report a positive and increasing trend for the CARs accumulated over varying periods subsequent to the end of "buy" trade packages. In particular, the CARs accrued over the initial 10-day period exhibit both statistical and economic significance. In contrast, CARs accumulated over periods subsequent to the end of "sell" trade packages are always negative. Overall, these results provide further confirmation that, collectively, active Australian small-cap equity managers are successful stock pickers. The first ten days subsequent to the end of "buy" trade packages are the most

[21] It is assumed that there are 22 trading days in a month.

significant period over which private information possessed by small-cap managers is released to the market. Thus, there is a clear indication that abnormal returns earned as result of superior stock-selection ability is mostly concentrated over a short period of time. These findings provide further motivation for the use of daily trading data in performance evaluation.

<<INSERT TABLE 8>>

Next, we extend Table 8 to examine abnormal returns from daily trading data according to relative trade size. Our results are reported in Table 9. As the absolute trade size definition fails to control for the size of the fund undertaking the trade, we also conduct a relative trade size test measured as the ratio of a fund's trade package and month *t-1* total fund assets. Both the "Medium" and "Large" trade categories generate the highest abnormal returns over the 60-day evaluation period, equal to 127 and 120 basis points, respectively, while the "Small" trade category accumulates 87 basis points. However, the CARs over the initial ten days illustrate that "Small" and "Medium" size trades outperform "Large" size trades. The CARs for stocks sold in both the "Small" and "Medium" trade partitions are almost always negative, whereas, the results for the sales of the "Large" trade partition are always positive. The evidence therefore suggests that active small-cap equity managers are perhaps selling prematurely.

<<INSERT TABLE 9>>

4.3 Results of Returns-Based Estimations

This section reports the results derived from employing returns-based analysis for a larger sample of institutional funds captured in the Mercer Investment Consulting universe of managers. Our motivation for these tests is to provide comparisons to the measures of performance documented above, as well as to consider performance metrics that have been used extensively in the literature. The returns provided by the funds to Mercer Investment Consulting are gross of management

expenses but net of market impact costs (as these are the returns that the investors actually achieve). To arrive at a net performance figure after all costs, a management expense ratio needs to be deducted from the gross return.[22] The average management expense ratio for institutional small-cap funds in Australia is approximately nine basis points per month (or 1.08 percent per annum).

Table 10 presents the regression estimates derived from a four-factor model that accounts for the small companies' market proxy, stock size, book-to-market ratio and past price momentum. We provide the results of these additional returns-based performance tests to determine whether managerial skill is explained by a fund's exposures to factor loadings on stock size, book-to-market, momentum and liquidity. Our results provide further support that active Australian small-cap equity managers collectively possess skill in stock selection. Small-cap managers on average outperform the benchmark by an economically significant 68 basis points per month (or 8 percent per-annum) for the four-factor model, which declines to 59.6 basis points when we consider a five-factor model controlling for market liquidity.[23,24]

<<INSERT TABLE 10>>

4.4 Benchmark Index Robustness Test

To further validate the robustness of the returns-based results, we redefine the benchmark portfolio of different regressions using the All Ordinaries Index (a broader index including large-cap stocks) rather than the Small Ordinaries Index. In unreported results, the performance analysis using the All Ordinaries Index as the benchmark shows that fund managers remain capable of generating

[22] The management expense ratio accounts for all costs including brokerage, custody, administration and management expenses.

[23] In unreported results, a different version of the "illiquidity" factor (i.e., relative bid-ask spread was also used to proxy for liquidity) was also tested to ensure that the results are robust. These results were consistent with the findings presented in this study.

[24] We also conducted conditional performance evaluation model tests in the spirit of Ferson and Schadt (1996). In unreported results, the conditional alphas were also of a similar magnitude to the performance estimates using unconditional multi-factor models.

economically significant abnormal returns. In particular, the average monthly alpha ranges from 66.3 basis points (five-factor model) to in excess of 77.4 basis points (three-factor model).[25]

4.5 Transaction Cost Considerations

Overall, there is overwhelming evidence to support the proposition that active Australian small-cap equity managers possess superior skill in identifying and exploiting mispriced securities. However, all the performance estimates discussed thus far are calculated on a pre-expense basis. While explicit costs charged by investment managers (i.e., management fees on average were 8.4 basis points per month) still lead us to conclude that the alphas are economically significant, the analysis of the size of implicit costs is also of significant interest. It is important to note that the performance results presented in this study already account for price impact, as the returns generated are those actually achieved by the fund managers after market effects. While the measurement and analysis of transaction costs are beyond the scope of this study, recent research by Comerton-Forde *et al.* (2006), using the same dataset of fund transactions, finds that transaction costs are indeed significant, with a total price impact averaging 0.67 percent for purchases, and -0.62 percent for sales on a principal-weighted basis for S&P/ASX Small Ordinaries stocks. Consistent with smaller stocks exhibiting lower levels of liquidity, the magnitude of trading costs documented by Comerton-Forde et al. (2006) reveals higher estimates than in previous research. The round-trip cost of a trade in small-cap stocks is 1.29 percent, whereas earlier studies by Aitken and Frino (1996) and Comerton-Forde et al. (2005) show that larger stocks on the ASX incur trade costs of 0.27 percent and 0.50 percent, respectively.

5. Conclusion and Suggestions for Future Research

Our study examines actively managed small-cap equity funds in Australia using a unique database of portfolio holdings and transactions. Our study is the first to examine active portfolio management in smaller stocks within the Australian market. Consistent with the international evidence, we find

[25] Furthermore, the results of conditional as well as fund flow measures tested against the All Ordinaries Index remain highly comparable with the results tested against the Small Ordinaries Index.

evidence of superior stock-selection ability in the Australian small-cap equity market. Interestingly, the magnitude of abnormal returns remains economically significant, even after accounting for transaction costs. Performance is also found to be consistent across various risk models, including our research design which relies on more granular measures of performance sourced from portfolio holdings and transactions data.

In our study, the comparatively lower levels of efficiency in the Australian small-cap equity market may well help us to explain the size of the alphas generated by small-cap managers. Small-cap stocks have lower analyst coverage, and limited coverage may result in these stocks having lower levels of market efficiency. Alternatively, some may link the success of the industry to the significant funds flowing into the Australian small-cap equity market over the last few years. Indeed, Warther (1995) finds that monthly fund returns are strongly correlated with concurrent unexpected fund flows, which suggests there is a positive relationship between fund inflows and the subsequent returns generated by portfolios. In addition, larger market participants may also exercise increasing influences over the performance of stocks given their relative size on the register of smaller companies, which may lead to price inflation concerns similar to those documented by Carhart *et al.* (2002). Their research suggests that price inflation around quarter-end is around two percent per year for small-cap stocks. It goes without saying that future research is warranted concerning the drivers of outperformance in small-cap equity management.

References

Acharya, V., Pedersen, L., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410.

Aitken, M., Ferris, G., 1991. A note on the effect of controlling for transaction costs on the small firm anomaly: Additional Australian Evidence. Journal of Banking and Finance 15, 1195-1202.

Aitken, M., Frino, A., 1996. Execution costs associated with institutional trades on the Australian Stock Exchange, Pacific-Basin Finance Journal 4, 45-58.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223-249.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31-56.

Banz, R.W., 1981. The relationship between return and market value of common stocks. Journal of Financial Economics 9, 3-18.

Bennett, J.A., Sias, R.W., Starks, L.T., 2003. Greener pastures and the impact of dynamic institutional preferences. Review of Financial Studies 16, 1203-1238.

Blume, M.E., Stambaugh, R.F., 1983. Biases in computed returns: An application to the size effect. Journal of Financial Economics 12, 387-404.

Brennan, M.J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specification, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics 49, 345-373.

Brennan, M.J., Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. Journal of Financial Economics 41, 441-464.

Brown, P.R., Keim, D.B, Kleidon, A.W., Marsh, T.A., 1983. Stock return seasonalities and the tax-loss selling hypothesis: Analysis of the arguments and Australian evidence. Journal of Financial Economics 12, 105-127.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Carhart, M.M., Kaniel, R., Musto, D.K., Reed, A.V., 2002. Leaning for the tape: Evidence of gaming behaviour in equity mutual funds. Journal of Finance 57, 661-693.

Chakravarty, S., 2001. Stealth trading: Which traders' trades move stock prices? Journal of Financial Economics 61, 289-307.

Chan, H., Faff, R.W., 2003. An investigation into the role of liquidity in asset pricing: Australian evidence. Pacific-Basin Finance Journal 11, 555-572.

Chan, L.K.C., Lakonishok, J., 1995. The behavior of stock prices around institutional trades. Journal of Finance 50, 1147-1174.

Chen, H-L., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. Journal of Financial and Quantitative Analysis 35, 343-368.

Chiyachantana, C.N., Jain, P.K., Jiang, C., Wood, R.A., 2004. International evidence on institutional trading behavior and price impact. Journal of Finance 59, 869-898.

Chordia, T., Subrahmanyam, A., Anshuman, V.R., 2001. Trading activity and expected stock returns. Journal of Financial Economics 59, 3-32.

Christopherson, J., Ding, Z., Greenwood, P., 2002. The perils of success. Journal of Portfolio Management 28, 41-53.

Comerton-Forde, C., Fernandez, C., Frino, A., Oetomo, T., 2005, How broker ability affects institutional trading costs, Accounting and Finance 453, 351-374.

Comerton-Forde, C., Gallagher, D.R., Nahhas, J., Walter, T.S., 2006. Transaction costs and institutional trading: An examination of small-cap equity funds. Working Paper, The University of Sydney.

Dahlquist, M., Engström, S., Söderlind, P., 2000. Performance and characteristics of Swedish mutual funds. Journal of Financial and Quantitative Analysis 35, 409-423.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035-1058.

Elton, E.J., Gruber, M.J., Das, S., Hlavka, M., 1993. Efficiency with costly information: A reinterpretation of evidence from managed portfolios. Review of Financial Studies 6, 1-22.

Elton, E.J., Gruber, M.J., Blake, C.R., 1996. The persistence of risk-adjusted mutual fund performance. Journal of Business 69, 133-157.

Engström, S., 2004, Does Active Portfolio Management Create Value? An evaluation of fund managers' decisions. Working Paper, Stockholm School of Economics.

Ferson, W.E., Schadt, R., 1996. Measuring fund strategy and performance in changing economic conditions. Journal of Finance 51, 425-461.

Fouse, W.L., 1989. The "small stock" hoax. Financial Analysts Journal 45, 12-15.

Frino, A., Gallagher, D., Oetomo, T., 2006. Further analysis of the liquidity and information components of institutional orders: Active versus passive funds. Pacific-Basin Finance Journal 14, 439-452.

Frino, A., Jarnecic, E., Johnstone, D., Lepone, A., 2005. Bid-ask bounce and the measurement of price behavior around block trades on the Australian Stock Exchange. Pacific-Basin Finance Journal 13, 247-262.

Gallagher, D.R., Looi, A., 2006. Trading behaviour and the performance of daily institutional trades. Accounting and Finance 46, 125-147.

Gorman, L., 2003. Conditional performance, portfolio rebalancing, and momentum of small cap mutual funds. Review of Financial Economics 12, 1-14.

Gregory, A., Matatko, J., Tonks, I., Purkis, R., 1994. UK directors trading: The impact of dealings in smaller firms. Economic Journal 104, 37-53.

Grinblatt, M., Titman, S., 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. Journal of Business 62, 393-416.

Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. American Economic Review 70, 393-407.

Gruber, M.J., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 55, 783-810.

Jensen, M.C., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389-416.

Keim, D.B., 1999. An analysis of mutual fund design: The case of investing in small-cap stocks. Journal of Financial Economics 51, 173-194.

Keim, D.B., Madhavan, A., 1997. Transaction costs and investment style: An inter-exchange analysis of institutional equity trades. Journal of Financial Economics 46, 265-292.

Klein, R.W., Bawa, V.S., 1977. The effect of limited information and estimation risk on optimal portfolio diversification. Journal of Financial Economics 5, 89-111.

Kothari, S. P., Warner, J.B., 2001. Evaluating mutual fund performance. Journal of Finance 56, 1985-2010.

Malkiel, B.G., 1995. Returns from investing in equity mutual funds 1971 to 1991. Journal of Finance 50, 549-572.

Otten, R., Bams, D., 2002. European mutual fund performance. European Financial Management 8, 75-101.

Pástor, L., Stambaugh, R., 2002a. Mutual fund performance and seemingly unrelated assets. Journal of Financial Economics 63, 315-349.

Pástor, L., Stambaugh, R., 2002b. Investing in equity mutual funds. Journal of Financial Economics 63, 351-380.

Pástor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Pinnuck, M.L., 2003. An examination of the performance of the trades and stockholdings of fund managers: Further evidence. Journal of Financial and Quantitative Analysis 38, 811-828.

Reinganum, M.R., 1981. Misspecification of capital asset pricing empirical anomalies based on earning yields and market value. Journal of Financial Economics 9, 19-46.

Reinganum, M.R., 1982. A direct test of Roll's conjecture on the firm size effect. Journal of Finance 37, 27-35.

Roll, R., 1981. A possible explanation of the small firm effect. Journal of Finance 36, 879-888.

Roll, R., 1983. *Vas ist Das*? The turn of the year effect and the return premia of small firms. Journal of Portfolio Management 9, 18-28.

Sinquefield, R.A., 1991. Are small-stock returns achievable? Financial Analysts Journal 47, 45-50.

Stoll, H.R., Whaley, R., 1983. Transaction costs and the small-firm effect. Journal of Financial Economics 12, 57-79.

Warther, V.A., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39, 209-235.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs and expenses. Journal of Finance 55, 1655-1695.

Table 1
Cross-Sample Comparisons

Panel A reports the mean gross-return generated by sub-sample sets of funds from the inception of each fund to 31 March 2004. Panel B presents the non-risk-adjusted returns-based performance estimates, calculated as the difference between the gross return generated by small-cap equity funds and the benchmark return (S&P/ASX Small Ordinaries Accumulation Index). Panel C presents the risk-adjusted performance estimates using the single-factor model:

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \varepsilon_{i,t}$$

where $r_{i,t}$ and $r_{m,t}$ are the raw monthly excess-returns of fund *i* and the ASX/S&P Small Ordinaries Accumulation Index, respectively, over the one-month risk-free rate from the Reserve Bank of Australia (RBA), α_i is the unconditional Jensen alpha and $\beta_i's$ are the factor loadings. All return metrics are calculated on a monthly basis and expressed in percentages. "Full Sample" refers to the complete small-cap universe as defined by Mercer (40 funds). "Sample A" refers to the sample of funds with at least 12 consecutive monthly returns (34 funds). "Sample B" refers to the sample of funds which provided information on their monthly holdings and daily transactions (12 funds).

Cross-Sample Comparison of Monthly Fund Performance			
Panel A: Gross Return			
	Full Sample	Sample A	Sample B
Mean Return	1.808	1.565	1.693
Std. Dev	0.882	0.647	0.690
t-statistics	-	1.331	0.416
No. Sign and Pos	32	27	10
Total No. of Funds	40	34	12
Panel B: Gross Minus Benchmark (Non-risk adjusted)			
	Full Sample	Sample A	Sample B
Mean Return	0.781	0.679	0.959
Std. Dev	0.647	0.617	0.658
t-statistics	-	0.692	0.831
No. Sign and Pos	28	23	9
Total No. of Funds	40	34	12
Panel C: Jensen's Alpha (Risk-adjusted)			
	Full Sample	Sample A	Sample B
Alpha (α)	-	0.761	1.010
Std. Dev	-	0.594	0.630
t-statistics	-	-	1.315
No. Sign and Pos	-	26	9
Total No. of Funds	-	34	12

* t-statistic tests whether the performance of the sub-samples is significantly different from zero.

Table 2

Monthly Holdings of Small-Cap Fund Managers

This table shows the monthly holdings of small-cap fund managers from January 1996 to March 2004. Panel A reports the average number of holdings (i.e., number of stocks held) per month. Panel B reports the monthly proportion of holdings calculated based on holding values in stocks included in the S&P/ASX 100 Index, S&P/ASX Small Ordinaries Index, and micro-cap stocks (outside S&P/ASX 300) listed on the Australian Stock Exchange. Panel C reports the break-down of funds' holdings in small-cap stocks by company size from smallest (Q1) to largest (Q4).

Monthly Holdings of Small-Cap Fund Managers					
Panel A: Number of holdings per month					
	Mean	Std. Dev	Lower Quartile	Median	Upper Quartile
Number of Stocks Held	35.52	16.40	25.47	36.76	42.55
Panel B: Proportion of holdings per month					
	Mean	Std. Dev	Lower Quartile	Median	Upper Quartile
S&P/ASX 100 (%)	9.94	12.88	1.55	2.20	16.55
Small Ordinaries (%)	72.43	16.04	54.99	77.81	85.39
Micro-Caps (%)	17.63	12.96	11.15	17.23	19.50
Panel C: Proportion of holdings per month within small-cap stocks					
Q1 (%)	4.12	3.03	1.20	4.12	6.46
Q2 (%)	14.51	5.03	11.12	15.27	17.57
Q3 (%)	20.97	4.74	16.37	21.86	25.76
Q4 (%)	32.84	17.26	19.17	31.75	41.38
Total (%)	72.43	16.04	54.99	77.81	85.39

Table 3

Summary Statistics for Transactions-Based Data

Trade packages are defined as either a series of purchases or sales made by managers in the same stock, where the number of trading days between consecutive trades is no more than four days. Panel A and Panel B present the frequency distribution of both trade packages and their associated market value. "Packs" refers to the percentage of trade packages completed within the indicated number of days, and "Value" refers to the ratio of total trading activity to the underlying dollar value of trades completed in the period. Panel C provides the annual summary statistics of daily trading activities of 11 active Australian small-cap equity managers over the period January 1998 to March 2004. Turnover refers to the average turnover of all funds in the sample for the respective year, where turnover for a specific fund *i* is defined as the sum of all trades of fund *i* in year *t divided by the* average size of fund *i* in year *t*.

Statistics for Trade Packages in the Period January 1998 to March 2004										
Size Quartiles	1 Day		2-3 Days		4-6 Days		7-10 Days		>11 Days	
	Packs	Value	Packs	Value	Packs	Value	Packs	Value	Packs	Value
Panel A: Buys										
Q1 (%)	15.85	9.56	2.95	3.29	3.42	5.00	2.22	4.02	1.16	3.63
Q2 (%)	30.72	18.82	10.43	9.71	7.42	9.94	2.07	4.96	2.58	10.75
Q3 (%)	9.96	5.84	2.76	2.64	2.14	2.72	1.47	3.69	0.43	2.28
Q4 (%)	3.50	1.74	0.40	0.28	0.35	0.63	0.08	0.04	0.08	0.46
Total	60.03	35.96	16.54	15.92	13.33	18.30	5.84	12.71	4.26	17.11
Panel B: Sells										
Q1 (%)	12.99	8.45	2.20	1.65	3.54	4.21	0.28	0.35	0.78	1.74
Q2 (%)	29.41	20.57	12.82	10.48	7.30	8.98	4.48	7.93	4.18	11.95
Q3 (%)	9.27	6.78	3.26	3.92	2.28	3.40	0.96	1.46	1.04	3.07
Q4 (%)	3.39	1.98	0.45	0.41	0.56	0.61	0.74	1.42	0.08	0.63
Total	55.06	37.78	18.72	16.47	13.68	17.21	6.46	11.15	6.08	17.39
Panel C: Summary Statistics										
			1998	1999	2000	2001	2002	2003	2004 (to March)	Years 1998-2003
Total Dollar Value of Buy Packs (A$,000)			15,146	35,147	132,152	497,467	748,795	1,068,031	215,992	2,496,738
Total Dollar Value of Sell Packs (A$,000)			4,044	12,173	83,874	349,811	643,553	853,429	214,784	1,946,884
Average Value of Buy Packs (A$,000)			72	106	210	362	317	342	382	235
Average Value of Sell Packs (A$,000)			81	112	319	459	391	324	362	281
Std. Dev of the Value of Buy Packs (A$,000)			353	163	486	631	500	588	607	454
Std. Dev of the Value of Sell Packs (A$,000)			328	120	442	951	568	572	860	497
No. of Buy Packs			209	333	629	1375	2365	3120	566	8031
No. of Sell Packs			50	109	263	762	1644	2630	594	5458
No. of Buy Trades			271	478	1062	2995	5786	8470	1534	19062
No. of Sell Trades			59	156	490	1584	4623	8101	1690	15013
Turnover (%) p.a. = (∑buys + sells)/average fund size			136.51	102.03	126.02	164.41	172.25	237.04	n/a	156.38

Table 4

The Relative Trading Activity for Small-Cap Stocks on the Australian Stock Exchange (ASX)

This table reports the average daily trading activity for a typical stock included in the S&P/ASX 100 Index, S&P/ASX Small Ordinaries Index, and micro-cap stocks (outside S&P/ASX 300) listed on the Australian Stock Exchange. The reported variables include the average daily trade value, the average daily trade volume, the average daily trade frequency and the average daily off-market volume for a typical stock in each category. In addition, a comparison of the proportion of trading activity is also provided. Results are reported for the last four years and the last 12 months to 30 June 2004.

Daily Average Trading Activities for a Typical Stock in the Respective Sectors					
Panel A: 4 Years to 30 June 2004					
Indices	Avg. Daily Value	Avg. Daily Trade Volume	Avg. Daily Trade Frequency	Off-Market Volume	Average Number of Stocks
S&P/ASX All Ordinaries	13,829,471	2,840,165	427	963,102	492
S&P/ASX 100	13,104,576	2,110,604	353	763,445	101
S&P/ASX Small Ordinaries	543,784	470,263	58	161,513	186
Micro-Caps	181,111	259,298	16	38,144	101
Small Ordinaries/ASX 100 (%)	4.14	22.28	16.43	21.16	1.84
Micro-Caps/ASX 100 (%)	1.38	12.29	4.53	5.00	1
Panel B: 12 Months to 30 June 2004					
S&P/ASX All Ordinaries	17,035,942	3,824,507	494	1,206,024	491
S&P/ASX 100	15,967,542	2,671,994	402	924,851	100
S&P/ASX Small Ordinaries	803,995	690,594	70	214,260	187
Micro-Caps	264,405	461,919	22	66,913	100
Small Ordinaries/ASX 100 (%)	5.04	25.85	17.41	23.17	1.87
Micro-Caps/ASX 100 (%)	1.66	17.29	5.47	7.23	1

Table 5

Holdings-Based Performance Measures

This table presents the performance of small-cap equity funds using holdings-based measures. The event window for this analysis is from January 1998 to March 2004. The mean abnormal return is the average of the monthly abnormal returns generated by small-cap managers in the sample, whereby the monthly abnormal returns of individual managers are calculated on a value-weighted basis using the individual abnormal returns generated by the underlying stocks held by the managers. The weight assigned is determined by the value, in dollar terms, of the underlying position in each stock relative to the aggregate portfolio as at the end of the month. This weight then remains constant throughout subsequent evaluation periods. Adjustment for risk is made using the characteristic-matched benchmark portfolios. The abnormal return for a particular stock in a particular month is calculated as the monthly difference between the buy-and-hold return of the underlying stock and the buy-and-hold return of a value-weighted portfolio of stocks having similar characteristics across the risk dimensions of "size", "book-to-market" and "momentum". Algebraically, the abnormal return for manager *j* in month *t* is defined as follows;

$$AR_{jt} = \sum_{i=1}^{N} w_{i,t-1}(r_{i,t} - r_t^{DGTW(i),t-1}) \tag{6.11}$$

where $w_{i,t-1}$ is the portfolio weight for stock *i* at the end of month *t – 1*, $r_{i,t}$ is the month *t* return of stock *i*, and $r_t^{DGTW(i),t-1}$ is the month *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* during month *t – 1*. All return-related measures are expressed in percentages.

Holdings-Based Performance Estimates						
	Event Time					
	AR+1	AR+2	AR+3	AR+4	AR+5	AR+6
Mean	0.384	0.275	0.280	0.165	0.212	0.101
t-statistics	2.46 **	1.81 *	1.82 *	1.05	1.40	0.64
Std. Dev	3.528	3.437	3.468	3.524	3.390	3.492
Maximum	20.257	19.171	18.372	17.068	15.566	16.719
Minimum	-25.177	-25.108	-20.410	-23.064	-19.602	-22.213
No. Positive (%)	60.27	57.48	57.22	54.69	54.52	51.62
No. Negative (%)	39.73	42.52	42.78	45.31	45.47	48.38
Total Observations	511	508	505	501	497	492
CAR	0.384	0.659	0.939	1.104	1.316	1.417

***, **, and * indicate significance at the 1%, 5% and 10% (two-tail) level, respectively.

Table 6

Holdings-Based Inferred Trade Performance Measures

This table presents the results derived from inferred trade measures. Trade is inferred from changes in the level of portfolio holdings between consecutive months, where a positive change implies a buy trade and a negative change implies a sell trade. Algebraically, inferred trade can be computed using the following equation:

$$IT_{ijt} = w_{ijt} - w_{ijt-1}$$

where IT_{ijt} refers to the inferred trade measure for stock *i* of manager *j* at time *t*, and w_{ijt} and w_{ijt-1} refer to the portfolio weights for stock *i* at the end of months *t* and *t – 1* respectively. Using the trade metric value, inferred trades are further partitioned into sub-samples of "buy" and "sell" trades. The mean abnormal return for each partition represents the average of the monthly abnormal returns of small-cap managers in the sub-sample, calculated on a value-weighted basis using the abnormal returns of stocks held by the managers. Panel B presents the results derived from holdings-based inferred trade performance measures decomposed according to trade size. Three different categories of trade size are employed - "Large" trade is defined as a trade that has an underlying dollar value greater than A$1,000,000, a "Medium" trade is defined as a trade with an underlying dollar value between A$100,000 and A$1,000,000 and a "Small" trade is a trade with a value less than A$100,000. The mean abnormal return for each partition represents the average of the monthly abnormal returns of small-cap managers in the sub-sample, calculated on a value-weighted basis using the abnormal returns of stocks held by the managers. "Weight" refers to the percentage of stocks categorised into each respective trade size category. All return-related measures are expressed in percentages.

		Event Time						
		AR+1	AR +2	AR +3	AR +4	AR +5	AR +6	Weight (%)
Panel A: Holdings-Based Inferred Trade Performance Estimates								
Buys								
Mean		0.597	0.238	0.369	0.163	0.279	0.167	-
t-statistics		2.28 **	0.79	1.09	0.57	1.12	0.63	-
Std. Dev		5.761	6.582	7.430	6.195	5.417	5.671	-
Maximum		27.989	41.494	42.689	23.241	20.706	20.025	-
Minimum		-28.181	-59.411	-81.694	-35.974	-25.513	-45.428	-
No. Positive (%)		56.28	56.96	55.02	54.01	51.70	54.83	-
Total Observations		485	481	478	474	470	465	-
CAR		0.597	0.835	1.204	1.367	1.646	1.813	-
Sells								
Mean		-0.141	-0.709	-0.081	0.022	-0.353	-0.084	-
t-statistics		-0.37	-1.65 *	-0.26	0.07	-0.99	-0.29	-
Std. Dev		7.750	8.784	6.248	5.960	7.165	5.849	-
Maximum		28.827	26.524	19.774	45.541	31.068	26.280	-
Minimum		-55.814	-87.568	-33.935	-24.944	-39.946	-20.410	-
No. Positive (%)		50.00	49.40	48.66	46.56	44.19	50.75	-
Total Observations		420	417	413	408	405	398	-
CAR		-0.141	-0.850	-0.931	-0.909	-1.262	-1.346	-
Panel B: Holdings-Based Inferred Trade Performance Estimates - Trade Level Breakdown								
Buys								
Large	Mean	-0.184	0.599	1.180	-0.422	-0.021	0.125	17.01
	t-statistics	-0.44	1.34	2.11 **	-0.72	-0.05	-0.27	
Medium	Mean	1.254	-0.096	0.071	0.506	0.219	0.097	55.96
	t-statistics	3.12 ***	-0.30	0.21	1.91 *	0.88	0.38	
Small	Mean	0.386	0.107	0.185	0.430	-0.093	-0.945	27.03
	t-statistics	0.79	0.24	0.32	0.87	-0.23	-1.48	
Sells								
Large	Mean	0.240	0.776	-0.702	0.296	-0.886	-0.444	18.31
	t-statistics	0.55	1.38	-1.45	0.70	-1.79 *	-0.50	
Medium	Mean	-0.223	-0.963	0.008	0.288	-0.093	-0.139	54.98
	t-statistics	-0.55	-2.30 **	0.02	0.35	-0.25	-0.44	
Small	Mean	-0.967	-0.883	-0.607	-0.726	-1.236	-0.062	26.71
	t-statistics	-1.88 *	-1.57	-0.73	-0.89	-1.70 *	-0.12	

***, **, and * indicate significance at the 1%, 5% and 10% (one-tail) level, respectively.

Table 7

Transactions-Based Performance Measures (Abnormal Returns)

This table presents the results derived from transactions-based performance measures. Specifically, this table reports the average of the mean daily abnormal returns for the respective evaluation periods. The mean abnormal return for a particular day is calculated on an equally-weighted basis as the average of daily abnormal returns for all trade packages in the sample for that day. The daily abnormal return for a single trade package is calculated as the difference between the one-day buy-and-hold return of the underlying stock in the package and the one-day buy-and-hold return of a value-weighted portfolio of stocks having similar characteristics across the risk dimensions of "size", "book-to-market" and "momentum" as the stock under examination. Algebraically, the mean daily abnormal return for day *t* is calculated as follows;

$$\overline{AR_t} = \sum_{j=1}^{L} \sum_{t=1}^{D_j} (r_{ij,t} - r_t^{DGTW(ij),t-1}) \Big/ N$$

where $\overline{AR_t}$ is the mean daily abnormal return for day *t*, $r_{ij,t}$ is the day *t* return of stock *i*, $r_t^{DGTW(ij),t-1}$ is the day *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* for manager *j* on day *t*, *L* represents the total number of underlying stocks traded across the entire sample, D_j represents the number of multiple trade packages in the same stock across different time periods and managers, and *N* is the total number of trade packages in the entire sample. Note that the daily abnormal returns calculated over the window [Day (-60 to 0)] utilise the start date of a trade package as the reference date, while the daily abnormal returns calculated over the window [Day (0 to +60)] utilise the end date of a trade package as the reference date. All return-related measures are expressed in percentages.

Summary Statistics of Mean Daily Abnormal Returns Over the Event Window [Day (-60 to +60)]				
	Day (-60 to 0)		Day (0 to +60)	
	Buy	Sell	Buy	Sell
Mean Abnormal Return	0.042	0.027	0.021	-0.006
Std. Dev	0.044	0.037	0.036	0.044
Maximum	0.142	0.120	0.192	0.094
Minimum	-0.103	-0.101	-0.039	-0.153
No. of Days with Positive Abnormal Returns	54	48	42	32
No. of Days with Negative Abnormal Returns	6	12	18	28
No. of Days with Significant and Positive Abnormal Returns	29	18	16	2
No. of Days with Significant and Negative Abnormal Returns	2	2	0	5

Table 8

Transactions-Based Performance Measures (CARs)

This table presents the results derived from transactions-based performance measures. Cumulative abnormal returns (CARs) are calculated as the sum of individual daily mean abnormal returns over corresponding accumulation periods, whereby the mean daily abnormal returns are calculated on an equally weighted basis using the procedure outlined in Table 6. The CARs calculated over the period [Day (-60 to 0)] utilise the start date of a trade package as the reference date, while the CARs calculated over the period [Day (0 to +60)] utilise the end date of a trade package as the reference date. Algebraically, the CARs are calculated as follows;

$$CAR_T = \sum_{t=1}^{T} \overline{AR}_t$$

where CAR_T is the cumulative abnormal return measured between day *t* and day *T* inclusive and $\overline{AR_t}$ is the mean daily abnormal return for day *t*. Further, the *Z-statistics* for the CARs are calculated using an approach consistent with Gregory *et al*. (1994), who provide a correction for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

Transactions-Based Performance Estimates								
	Buys	Sells	Buys – Sells		Buys	Sells	Buys - Sells	
AR [-1][a]	0.142 ***	-0.020	0.162	AR [+1][a]	0.192 ***	-0.034	0.226	
CAR [-2;0]	0.058 ***	0.100 ***	-0.042	CAR [0;+2]	0.309 ***	-0.131 ***	0.440	
CAR [-3;0]	-0.045 ***	0.146 *	-0.191	CAR [0;+3]	0.390 ***	-0.116 *	0.506	
CAR [-4;0]	-0.057 ***	0.199 *	-0.257	CAR [0;+4]	0.414 ***	-0.165 *	0.579	
CAR [-5;0]	-0.036 ***	0.193 *	-0.229	CAR [0;+5]	0.465 ***	-0.071	0.536	
CAR [-10;0]	0.050 **	0.265	-0.215	CAR [0;+10]	0.576 **	-0.040	0.616	
CAR [-15;0]	0.227 *	0.377	-0.150	CAR [0;+15]	0.621	-0.211	0.832	
CAR [-20;0]	0.455	0.495	-0.041	CAR [0;+20]	0.641	-0.201	0.842	
CAR [-25;0]	0.763	0.542	0.221	CAR [0;+25]	0.747	-0.194	0.941	
CAR [-30;0]	0.901	0.704	0.198	CAR [0;+30]	0.866	-0.183	1.049	
CAR [-35;0]	1.212	0.853	0.359	CAR [0;+35]	0.894	-0.343	1.237	
CAR [-40;0]	1.465	1.002	0.463	CAR [0;+40]	1.016	-0.441	1.457	
CAR [-45;0]	1.666	0.933	0.733	CAR [0;+45]	1.030	-0.365	1.395	
CAR [-50;0]	2.002	1.179	0.823	CAR [0;+50]	1.099	-0.358	1.457	
CAR [-55;0]	2.206	1.432	0.774	CAR [0;+55]	1.230	-0.343	1.573	
CAR [-60;0]	2.499	1.606	0.892	CAR [0;+60]	1.248	-0.380	1.628	

***, **, and * indicate significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The statistical significance for abnormal return series (i.e., AR -60 and AR +1) is calculated using standard *t*-tests.

Table 9

Transactions-Based Performance Measure by Relative Trade Size (CARs)

This table presents the results derived from transactions-based performance measures decomposed by relative trade size, whereby relative trade size is measured using actual trade value divided by fund size. Three different categories of trade size are employed – the "Large" category contains the largest 33% of trade packages in the sample, the "Medium" category contains the next 33% of trade packages in the sample, and the "Small" contains the remaining 33% of trade packages in the sample. Once the sub-samples are partitioned, the estimation procedure outlined in Table 7 is applied to compute the estimated values presented in the table. Further, the *Z-statistics* for the CARs are calculated using an approach consistent with Gregory *et al*. (1994), who provide a correction for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

Transactions-Based Performance Estimates - Relative Trade Size Decomposition												
	Buys						Sells					
	Small Trade		Medium Trade		Large Trade		Small Trade		Medium Trade		Large Trade	
CAR [-60;0]	0.960		3.354		3.723		0.977		1.559		1.966	
CAR [-50;0]	0.883		2.581		3.027		0.553		1.161		1.561	
CAR [-40;0]	0.384		1.766		2.624		0.690		0.741		1.344	
CAR [-30;0]	-0.108		1.128		1.983		0.421		0.760		0.740	
CAR [-20;0]	-0.479		0.770		1.245		0.378		0.519		0.428	
CAR [-10;0]	-0.593		0.236		0.619		0.267		0.260		0.222	
CAR [-5;0]	-0.421	***	0.047		0.341		0.340	**	0.173	**	0.004	
CAR [-4;0]	-0.409	***	0.069		0.250		0.427	***	0.108	***	0.004	
CAR [-3;0]	-0.426	***	0.087		0.263	*	0.341	***	0.079	***	-0.029	
CAR [-2;0]	-0.330	***	0.224	*	0.337	***	0.303	***	0.123	***	-0.161	
AR [-1][a]	-0.026	***	0.201	***	0.248	***	0.089		0.028		-0.176	**
AR [+1][a]	0.240	***	0.215	***	0.107	**	-0.212	***	0.032		0.073	
CAR [0;+2]	0.484	***	0.254	***	0.145	***	-0.350	***	-0.169	***	0.121	***
CAR [0;+3]	0.564	***	0.355	***	0.190	***	-0.407	***	-0.135		0.176	**
CAR [0;+4]	0.631	***	0.381	***	0.187	**	-0.478	***	-0.155		0.115	
CAR [0;+5]	0.679	***	0.499	***	0.161		-0.341		-0.020		0.124	
CAR [0;+10]	0.591		0.669		0.382		-0.490		0.080		0.259	
CAR [0;+20]	0.324		0.924		0.466		-0.866		-0.328		0.545	
CAR [0;+30]	0.315		1.164		0.767		-0.960		-0.438		0.817	
CAR [0;+40]	0.494		1.296		0.865		-1.669		-0.361		0.672	
CAR [0;+50]	0.629		1.227		0.974		-1.517		-0.247		0.648	
CAR [0;+60]	0.865		1.265		1.208		-1.409		-0.238		0.461	

***, **, and * indicate significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The statistical significance for abnormal return series (i.e., AR -60 and AR +1) is calculated using standard *t*-tests.

Table 10

Unconditional Multi-Factor Performance Measures

This table reports results estimated from the five-, four- and three-factor models over the period March 1995 to March 2004, March 1995 to March 2004, and June 1992 to March 2004, respectively. The dependent variables in these regressions are the time-series of monthly pre-expense excess-returns of the funds (over the one-month risk-free rate sourced from the RBA). The five independent variables are the monthly return of the Small Ordinaries Accumulation Index over the one-month risk free rate, the *SML* factor which is calculated as the difference in returns between the Small Ordinaries Index and the S&P/ASX 100 Index, the *GMV* factor which is calculated as the difference in returns between a growth and a value portfolio of stocks based on the Citigroup Global Markets Australian small-cap growth and value indices, the *PR1YR* factor which is constructed as the difference between the equally-weighted returns of two portfolios formed from either the top 20% or the bottom 20% of stocks on the Small Ordinaries Index ranked by their previous eleven-month returns lagged one-month, and the *IML* factor which is constructed as the difference between the equally-weighted returns of two portfolios formed from either the top 20% or the bottom 20% of stocks on the Small Ordinaries Index ranked by their average daily turnover in the previous month. All factors are recalculated on a monthly basis. All returns-related measures are expressed in percentages. α_i is a measure of stock-selection ability and β_i's are the factor loadings for the respective factors. Statistical significance is calculated at the 90% level and the *t-statistics* are calculated using White (1980) heteroskedastic-consistent standard errors.

	α		β_{SO}	β_{SML}	β_{GMV}	β_{PR1YR}	β_{IML}	*Adj* R^2
Panel A: Five-Factor Model								
Mean	0.596	***	0.890	-0.017	0.086	-0.028	-0.028	0.785
Std. Dev	0.519		0.202	0.166	0.376	0.240	0.094	-
Maximum	1.398		1.443	0.428	0.784	0.251	0.140	0.963
Minimum	-0.754		0.509	-0.352	-1.025	-1.344	-0.303	0.470
No. Positive	29		34	14	25	19	12	-
No. Significant and Positive	18		34	1	10	6	2	-
No. Significant and Negative	0		0	0	2	2	6	-
No. of Managers in the Sample	34		34	34	34	34	34	34
Panel B: Four-Factor Model								
Mean	0.680	***	0.885	-0.038	0.118	-0.038	-	0.735
Std. Dev	0.493		0.201	0.174	0.373	0.242	-	-
Maximum	1.947		1.407	0.402	0.983	0.156	-	0.939
Minimum	-0.357		0.486	-0.526	-0.882	-1.374	-	0.339
No. Positive	32		34	11	25	17	-	-
No. Significant and Positive	19		34	2	11	5	-	-
No. Significant and Negative	0		0	0	0	2	-	-
No. of Managers in the Sample	34		34	34	34	34	-	-
Panel C: Three-Factor Model								
Mean	0.638	***	0.902	-0.032	0.042	-	-	0.729
Std. Dev	0.589		0.167	0.127	0.311	-	-	-
Maximum	1.938		1.246	0.226	0.748	-	-	0.941
Minimum	-1.330		0.527	-0.273	-0.579	-	-	0.385
No. Positive	30		34	13	23	-	-	-
No. Significant and Positive	20		34	0	11	-	-	-
No. Significant and Negative	0		0	2	2	-	-	-
No. of Managers in the Sample	34		34	34	34	-	-	34

***, **, and * indicate significance at the 1%, 5% and 10% (two-tail) level, respectively.